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Motif Dynamics in the International Financial Network

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Abstract

Economic systems are increasingly built on interdependencies and the recent financial crisis put in evidence the issues arising from such market interconnections that can generate the collapse of the entire financial system. Of particular interest is understanding whether the temporal evolution of real economic networks topology is characterized by changes as a crisis manifests itself, and if such a changes are only temporary or permanent.

The goal of this paper is to clarify the interaction mechanisms between countries by detecting the characteristic dyadic and triadic network motifs (subgraphs of two and three vertices) associated to a particular business period in the International Financial Network (IFN).

We find that the crisis caused the topological property of the IFN to maximally deviate from random models which incorporate the local properties of the real network. We show that during financial distress most of the countries revise their relationships with their partners, reducing the number of reciprocal financial linkages. Finally we observe this behavior is only temporary, and the reversion to the mean trend suggests a return to a business as usual configuration.

Keywords: financial networks, network motifs, null models.
JEL Classification: D85, E65, F30, G01

1 *Introduction*

Economic and financial systems are populated by a multitude of actors (agents, banks, institutions, countries): all these entities do not act in isolation but are strongly linked by a complex set of interactions, exposed to both endogenous and exogenous fluctuations. The recent financial crisis put in evidence the issues arising from such market interconnections that can generate the collapse of the entire financial system.

A clear example is related to financial integration and globalization that widened the potential exposure to instability. The same international links that increased welfare and efficiency in recent decades served as a powerful propagation channel for financial and economic shocks during the 2007–09 crisis.

Part of the recent discussion has emphasized the role of international financial integration as a cause, and also a consequence, of the increased complexity of the global economic system. Indeed financial flows pose a threat to the extent that they contribute to vulnerabilities in the interconnected balance sheets of countries, financial institutions and firms around the world.

The analysis of economic and financial networks has been receiving a lot of attention (see [18], [2] and [6] among others). In particular, the search for regularities in the structures of financial networks (see [1]) is a topic recently addressed to reveal the relationships between such structural regularities and the function of networks.

The study of the international financial system has been developed by Kubelec and collaborators in [10], as well as Garratt and coworkers [8], who used the Bank for International Settlements (BIS) consolidated banking statistics to develop cross-border financial networks. In [13] McGuire and co-workers studied the international banking system while focusing in the cross-border financial trade. A similar approach was adopted in the study of global banking networks by Minoiu and Reyes in [16]. For several extreme phenomena taking place at the global economic level, they found enough evidence of incoming instabilities in the network regime.

In [6] Chinazzi et al. provided evidence on how the topology of countries' financial relationships can help to understand what happened after the financial shocks of 2008. By taking a network perspective to the study of the financial crisis, they assess the impact of the crisis on the topological properties of the *International Financial Network* (IFN), and show how network indicators can help explaining cross-country differences in the severity of the crisis.

Many of the financial networks have been shown to share global statistical properties, ranging from small world properties to scale-free behaviors (see [4], [5] and [7] among others). But to go beyond these features, would require an understanding of the basic structural elements particular to each class of networks. One important local property of networks are the so-called *network motifs*, which are defined as recurrent and statistically significant sub-graphs or patterns (see [14] and [15]).

More precisely network motifs are patterns of interconnections occurring in complex networks at numbers that are significantly higher than those in randomized networks while those occurring less frequently are called anti-motifs.

In the recent past, network motifs have attracted attention as a tool for studying directed networks. In biological networks, a small set of motifs appears to serve as basic building blocks of the entire network. Such motifs are believed to perform specific functional roles allowing an easily interpretable view of the entire known transcriptional network of the organism [19]. Related methods were used to test hypotheses on social networks in [9] and [26].

In economics and finance this technique is relatively new. Ohnishi and co-authors [17] identified characteristic patterns on Japanese inter-firm network for the year 2005. They found that V-shaped triads are network motifs, emphasizing that the taxonomy of industries obtained from the profiles is economically meaningful.

In [23], Squartini and Garlaschelli adopted an analytical pattern-detection method (see also [21]) to study the occurrence of triadic motifs in the World Trade Network (WTN). They found that motif characterizing the WTN are completely explained if the numbers of reciprocal edges are taken into account, underlying the evolution of the WTN is almost completely encoded into the dyadic structure.

More recently in [24] motif study has been employed to detect early-warning signals of topological collapse of the Dutch interbank networks. Looking at the evolution of many topological motif properties, authors show the crisis period was characterized by a sudden decrease of the abundance of full and empty dyads, and a sudden increase of the abundance of single dyads. By contrast, if the heterogeneity of banks' connectivity is controlled for, the same properties show a gradual transition to the crisis, starting in 2005 and are preceded by an even earlier period during which anomalous debt loops could have led to the underestimation of counter-party risk.

The goal of our paper is to clarify the interaction mechanisms between countries in the international economic system by detecting the characteristic network motifs associated to a particular business period. In particular, we identify the key topological properties of the IFN, from 2001 to 2012, that deviate from randomness. The evolutionary network approach provides direct empirical information about the interplay between the realized financial stress and the changes in the observed network structure.

We consider the IFN as a macro binary-directed (multi) graph where nodes are countries joined by directed links that connect the issuing country to the holder of the security (possibly disaggregated by type). Note that, even if a weighted network is more informative than its binary projection (the magnitude of the connections plays a quantitative role), recent empirical results, such as [22] and [25], have shown that the knowledge of the network binary structure is often more informative about a real-world economic network than the knowledge of the corresponding weighted property.

We carry out an empirical characterization of the interplay between realized financial stress and the changes in the observed financial network. For our analysis we employ the Coordinated Portfolio Investment Survey (CPIS), collected by the International Monetary Fund (IMF). Data include crossborder portfolio investment holdings of equity securities, long-term debt securities and short term debt securities listed by country of residence of issuer. We assess the impact of the crisis on the topological properties of the IFN, and we show how network motifs can help in explaining the differences in the impact of the crisis between different types of financial networks. We address two main questions: *does the topology of the IFN undergo major changes as a crisis suddenly manifests itself? Did any permanent or only temporary changes occur in the topology of the IFN during and after the crisis?*

We find that the crisis caused the topological property of the IFN to maximally deviate from random models which incorporate the local properties of the real network. We show that during financial distress most of the countries revise their relationships with their partners, reducing the number of reciprocal financial linkages. Finally we observe this behavior is only temporary, and the reversion to the mean trend suggests a return to a business as usual configuration.

The remaining of the paper is organized as follows. Section 2 describes the data we work with, emphasizing the primary role for the total portfolio investment network. In Section 3 we recall the main concepts about network motifs and the methodology adopted for the analysis; Section 4 presents the main results of the paper while Section 5 discusses the economic implications of our findings and concludes.

2 Data

The Coordinated Portfolio Investment Survey (CPIS), encompassing crossborder portfolio linkages among countries, provides a good insight of the global financial relationships. These statistics are collected by the IMF[1]. Data includes dif-

[1] Data are freely available at http://cpis.imf.org/

ferent type of country exposures, namely cross-border portfolio investment holdings of equity securities, long and short term debt securities listed by country of residence of issuer. We have complete bilateral data for roughly 80 countries for the period 2001–2012[2]. We analyze the topology of the IFN in five different cases: when the graph is built considering all financial investments (Total Portfolio Investments, TPI); when we consider only equity securities (ES); debt securities (TDS); long-term debt securities (LTDS) and short-term debt securities (STDS) as in [20]. More formally, we build a 5-layer binary-direct multigraph because we are interested in assessing unweighted relations. Each direct link is present if the original weight is positive and does not exist otherwise.

According to the IMF, portfolio investments are defined as cross border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets. A security is defined as a financial instrument that is designed to be traded, i.e., it is characterized by its negotiability.

Equity securities comprise all instruments and records that acknowledge claims on the residual value of corporations or quasi-corporations, after the claims of all creditors have been met. Shares, stocks and participations usually denote ownership of equity. Debt securities are negotiable instruments serving as evidence of a debt. They give the holders the unconditional right to fixed or contractually determined variable payments. The maturity of a debt instrument is clas-

[2] Data are available from 1997 but, since there are missing observations from 1998 to 2000, we select 2001 as the initial year for our analysis.

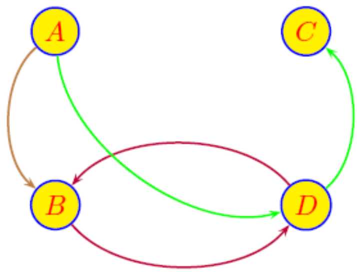

Figure 1: Total Portfolio Investment (TPI) layer structure: the graph is built considering all the financial exposures between countries. TPI is the union graph composed by ES, green links, TDS, brown and purple links, LTDS, brown links and STDS purple links.

sified as either long-term (a maturity of more than one year or with no stated maturity, other than on demand), or short-term (payable on demand or with a maturity of one year or less). Particular care is addressed in testing the hypothesis that the financial crisis results in a significant change of the IFN structure. To this extent it is primarily relevant to consider the TPI because the graph is built considering all the financial exposures between countries. On the other hand TDS consider all debt securities but not direct investment or reserve assets while ES, LTDS and STDS consider only equity securities, long-term debt securities and short-term debt securities respectively (see Figure 1).

3 Preliminary concepts and methods

3.1 Definitions

A directed graph $G = (V, E)$ consists of a finite set of vertices $V = \{v_1, ..., v_n\}$ and a finite set of edges $E = \{e_1, ..., e_m\}$ where each directed edge $e = (v_i, v_j)$ connects two vertices v_i, v_j called source and target vertex respectively. Let $(e_1, ..., e_k)$ be a sequence of edges in a graph G. This sequence is called a walk if there are vertices $v_0, ..., v_k$ such that $e_i = (v_{i-1}, v_i)$ for $i = 1, ..., k$. Two vertices u, v of a graph are called connected if there exists a walk from vertex u to vertex v. If any pair of different vertices of the graph are connected, the graph is called connected.

Two graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ are isomorphic, if there exists a bijective mapping between the vertices in V_1 and V_2, and there is an edge between two vertices of one graph if and only if there is an edge between the two corresponding vertices in the other graph. A graph $G' = (V', E')$ is a subgraph of a graph $G = (V, E)$ if $V' \subseteq V$, $E' \subseteq E \cap (V' \times V')$. A motif is a small graph G'. A match of a motif within a target graph G is a graph G'', which is isomorphic to the motif and a subgraph of G.

The number of non-isomorphic graphs grows exponentially with increasing size. Furthermore, there are up to $\left(\begin{array}{c} |E_m| \\ |E_t| \end{array} \right)$ matches of a motif $G_m = (V_m, E_m)$ in a graph $G_t = (V_t, E_t)$, where $|E_t|$ represents the number of edges in the target graph and $|E_m|$ is the number of edges in the motif.

In order to detect network motifs, it is necessary to count the number of appearances of all types of n-node subgraphs in the network. These results are *per se* entirely uninformative and can only be interpreted in relation to a null model which is a randomized graph that preserves only part of the topology of the observed network but it is maximally random.

Therefore we compare the real network to suitably randomized networks and only select patterns appearing in the real network at numbers significantly higher/lower than those in the null models.

3.2 Statistical significance of network motifs

According to [14], network motifs have been previously defined as patterns of interconnections occurring in networks at numbers that are significantly higher than those in randomized networks. To calculate the statistical significance of motifs' distribution in a target network, this distribution is compared against a random null hypothesis. For network motifs, the null hypothesis is represented by the distribution of motifs in an ensemble of appropriately randomized networks.

Rejection of the null hypothesis has been taken to represent evidence of functional constraints and design principles that have shaped network architecture at the level of the motifs.

3.2.1 Randomization algorithm for generation of null models

In our analysis we start using the so called *Directed Configuration Model* (DCM). The randomized networks produced by the null model have the exactly the single-node characteristics as does the real network: each node in the randomized networks has the same number of incoming and outgoing edges as the corresponding node in the real network.

The DCM indirectly maintains the real heterogeneity of countries by preserving the observed degrees produced by their heterogeneity. This provides a realistic benchmark with deviations indicating a genuine signature of higher-order effects beyond the country-specific level, directly arising from the turmoil affecting the economic environment.

As in [14] we apply a Markov-chain algorithm that switches randomly chosen pairs of connections of the real network until the network is well randomized. The algorithm reconnects two edges (v_1, v_2) and (v_3, v_4) in a way that v_1 becomes connected to v_4 and v_3 to v_2, provided that none of the newly created edges already exist in the network.

With this algorithm we scan the relative frequency of all possible n-node subgraphs with $n = 2, 3$ since we are primarily interested in dyadic and triadic motifs. Results are shown in the next section.

Furthermore, since triads are combinations of dyads, we also apply another null model to calculate the significance of 3-nodes subgraphs where the generated random network preserves the same number of appearances of all 2-nodes subgraphs as in the real network. This ensures that a high significance is not assigned to a pattern only because it has a highly significant sub-pattern, preventing the case in which some triadic motifs can be over(under)-represented just because the dyadic motifs they contain are over(under)-represented.

Such a null model is called *Reciprocal Configuration Model*

(RCM) and preserves the numbers of incoming, outgoing, and double edges with both incoming and outgoing arrows for each node. The RCM model considers double edges and single edges separately, allowing a double edge to be exchanged only with another double edge and only if the vertex are unconnected by an edge in any direction. Single directed edge swap are allowed only if they do not form new double edges.

3.2.2 Network motifs detection

In order to detect network motifs we apply the full enumeration method proposed in [14]. The algorithm count all connected n-node subgraphs in an adjacency matrix A looping through all rows i. Namely for each non-zero entry (i, j), it searches through all connected elements $A_{ik} = 1$, $A_{ki} = 1$, $A_{jk} = 1$, and $A_{kj} = 1$.

This is recursively repeated with elements (i, k), (k, i), (j, k), and (k, j) until an n-node subgraph is obtained. The number of appearances of each type of subgraph in the network are counted, correcting for the fact that multiple submatrices of A can correspond to one isomorphic architecture owing to symmetries. This process is repeated for each of the randomized networks. The number of appearances of each type of subgraph in the random ensemble is recorded, to assess its statistical significance. The network motif are those patterns for which the probability P of appearing in a randomized network an equal or greater number of times than in the real network, is lower than a cutoff value $P = 0.01$[3].

[3] Moreover it has to be noticed that patterns that are functionally important but not statistically significant could also exist.

3.2.3 Z-score computation

Statistical significance of motifs for a particular network can be measured by calculating the *z-score* and P-value using frequency concept. The frequency of a motif in a particular network is the number of different matches of this motif.

The z-score, see Eq. (1), is defined as the difference of the frequency of a motif in the target network and its mean frequency in a sufficiently large set of randomized networks, divided by the standard deviation of the frequency values for the randomized networks [12].

$$z_X \equiv \frac{X - \langle X \rangle}{\sigma\left[X\right]} \tag{1}$$

If the observed value of X corresponds to a large positive (negative) value of z_X then the quantity X is over (under)-represented in the data, and not explained by the null model. If X is normally distributed under the null model, then values within $z \pm 1$, $z \pm 2$, $z \pm 3$ would (approximately) occur with a 68%, 95%, 99% probability respectively. Even if the normality under the null model cannot be invoked for triads due to statistical dependencies among the random variables involved (triads necessarily share dyads, and are therefore not independent of each other), still larger z-scores identify more significant patterns[4].

[4] Even if null models do not represent, by themselves, a forecasting mechanism, it is nevertheless possible to detect a temporal trend, once the deviations highlighted by the z-scores analysis are plotted versus time. The resulting trends, clearly underlining an ongoing structural change, can be interpreted as the starting point of a predictive inference procedure.

Since we are mainly interested in the topological dynamics of the global financial network, we start looking for possible and noticeable structural changes and differences between business-as-usual and critical periods. In particular we focus on the TPI network because it considers all the financial kind of exposures between countries (see Figure 1).

Indeed the TPI is the *union* network defined as the combination of cross border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets. More formally, according to [3], given K networks $G_k = (V, E_k)$ with adjacency matrices $A_k = [a_k(i,j)]$, $k = 1, ..., K$, a union network $G_\cup = (V, E_\cup)$ is defined as follows: two nodes i and j are linked in $G_\cup$ if there exists a link between the two nodes at least in one of the K networks. The adjacency matrix $A_\cup$ of the union network is obtained by summing up $A_1, A_2, ..., A_K$. Accordingly, the TPI network allows to check the presence of any possible link between nodes and to detect topological signals of the crisis. We first focus on the relative frequency or abundance of all the possible dyadic and triadic motifs in the observed networks. These numbers are informative only after filtering out the real heterogeneity of countries. Such frequencies provide a realistic benchmark with deviations indicating signals of higher-order effects beyond the country-specific level, directly arising from the turmoil affecting the economic environment. Therefore we compare the appearances of each motif X in the target network with its mean frequency $\langle X \rangle$ under the DCM model. We introduce z-scores, as previously defined, to quantify the deviation between data and the null

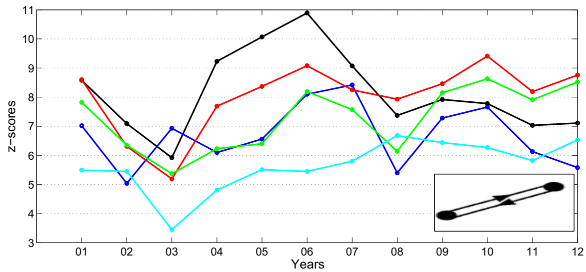

Figure 2: Reciprocated dyads in DCM model. Black line represents TPI, red TDS, blue ES, green LTDS and cyan STDS.

model.

Figure 2 shows the z-scores for the reciprocated dyads where different colors are assigned to different types of exposures. Three global trends are evident from the picture. Two decreasing phases in the years going from 2001 to 2003 and more prominent from 2006 to 2008, an almost stationary stage encompassing the years from 2009 to 2012, and an increasing phase going from 2003 to 2006. It has to be noticed that while the first years are still affected by the dot com bubble, the second decreasing phase is associated to the sub-prime financial crisis. This trend is more evident for the TPI network and for the TDS network.

The most significant deviations occur in the middle of the decade, with a prominent z-score decay for TPI from 2006 and during the early stage of the crisis; on the contrary, the STDS seems not to be affected in the same way. Thus, while the investment and debt securities behaviors have been strongly impacted by the crisis, equities remains closer to the mean with no evident trend.

These results suggest the financial crisis caused some countries to revise their relationships with their partners, reducing the number of reciprocal financial linkages. Furthermore, the z-score changes, associated to reciprocated dyads, are more pronounced in the period 2003-2008, whereas it appears to be less severe in the years after 2009. The findings underpin a sort of *reversion to the mean* movement, suggesting a return to the initial configuration[5].

Since the topological patterns captured by dyadic motifs are limited to correlations within pairs of vertices, we now analyze all the possible patterns involving three connected vertices, namely the triadic motifs ([14], [23]).

As we proceeded for the dyads, we analyze the z-scores of the 13 triadic motifs. However, before considering the development of individual z-scores over time, we first identify the most significant motifs looking at all the financial exposures between countries (i.e. the TPI network) by comparing all 13 z-scores with each other. This results in the motifs profile shown in Figure 3, where we used the DCM as the null model. In so doing we confront the evolution of all cross border transactions and positions over time. Looking at the red points which are referred to the years of the crisis (2006-2009), we can identify motifs 4, 5, 8, 10, 12 and 13 as the most significant ($|z| \gtrsim 5$) triadic signs at the onset of the crisis. In Figure 4 (left column) we track the temporal evolution of the relevant triadic motifs under the DCM null model. In all subplots it is evident that the STDS network displays sta-

[5]It has to be noticed that the single dyads (non reciprocated) have a behavior symmetrical with respect to the findings of figure 2 and, for this reason, we show only the full dyads.

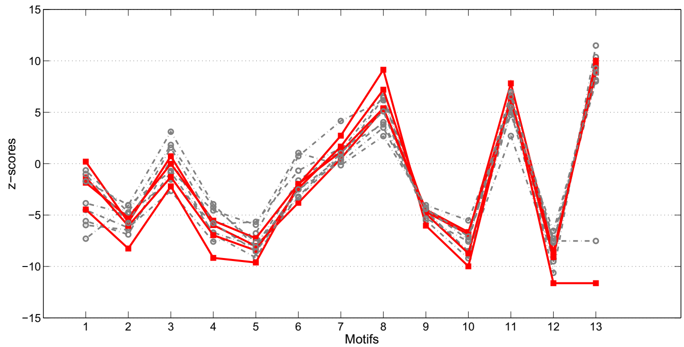

Figure 3: Triadic z-scores for the period 2001-2012 under the DCM. Red points represent the z-scores for the sub-period 2006-2009.

tistically non significant z-scores meaning that the Directed Configuration model is able to capture the triadic structure existent in the real STDS network, similarly to the behavior of the reciprocated dyads. Furthermore, as in Figure 2, the dynamics of the z-score for all other types of exposure remains close to each other during the first years of the sample and also in the final part, differently from the behavior observed during years 2003-2008. In particular starting from 2003, the z-score dynamics exhibits a reversion of the trend compared to the first years, which protracts until the beginning of the last financial crisis. Finally from 2008 we observe a return to the initial configuration where the z-scores of the different exposures are again close to each other.

Noteworthy that the TPI shows the most significant deviations from the initial state in all the triadic motifs as for the full dyads and, in general, it reaches the maximum or

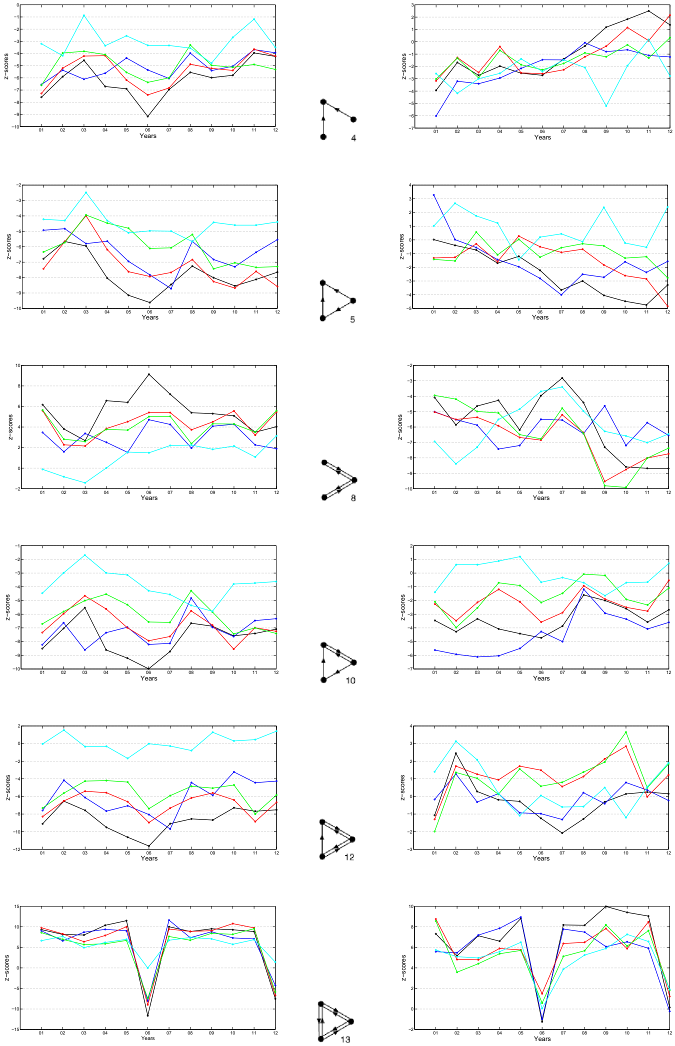

Figure 4: Temporal evolution of the triadic z-score for motifs 4, 5, 8, 10, 12, and 13 under the DCM (left column) and RCM (right column). Black line represents TPI, red TDS, blue ES, green LTDS and cyan STDS.

minimum value of the z-score one year in advance compared to the rest of the exposures. This behavior could be due to the fact that investments encompass all other exposures being more reactive to the changes that affect the economic environment.

To avoid that a high significance could be assigned to a pattern only because it has a highly significant sub-pattern, we consider another null model, called RCM, as we previously defined, that preserves the numbers of incoming, outgoing and double edges with both incoming and outgoing arrows for each node. This choice prevents the case in which some triadic motifs can be over(under)-represented just because the dyadic motifs they contain are over(under)-represented.

In Figure 4 (right column) we report the temporal evolution of the same motifs previously considered but under the RCM model. We find that, generally, the absolute value of the z-score associated to the triads is lower than its counterpart under DCM model. Motifs 4 and 5 are now no longer significative, displaying an increasing and decreasing trend respectively during the whole time sample, besides not being affected by the crisis. On the contrary, motif 12 shows the same course under both models exhibiting a rise of the z-score during financial distress years even if the boost is no more significant.

Thus most of the motifs can be better reproduced if also the numbers of reciprocal edges are taken into account. This implies the evolution of the IFN can be encoded into the dyadic structure, which strongly depends on reciprocity.

Nevertheless there are some exceptions. The dynamics of the other motifs are similar to the ones observed under the DCM null model. In particular motif 8 remains almost stationary until 2007 and then it exhibits a clear decreasing behavior more pronounced in the TPI but also remarkable in the TDS and LTDS. Motifs 10 in TDS, LTDS and STDS networks does not manifest any appreciable change because of its fluctuating trend whereas, in TPI and ES networks, it displays a perceptible modification during crisis years.

Finally motif 13 appears almost identical and significant in DCM and RCM models. Its trend is different from all the others being almost stationary in all the years, except for the biennium 2005-2007 and for the year 2011. The marked difference occurred just before the beginning of the crisis represents an anomaly phase in which the number of reciprocated triads turn out to be strongly under-represented.

5 *Discussion and concluding remarks*

The IFN is a particularly interesting network involving the global economy. The above results give insights on how the last financial crisis affected the exposures among countries.

Generally the dynamics of the z-score remains almost stationary during the first years of the new millennium and also in the final part of the sample, differently from the behavior observed during years 2003-2008. Importantly, our findings also suggest that during the build-up of crises the network can keep moving away from the trend that characterizes the business as usual configuration. The results about the dyadic motifs underline the financial crisis caused some countries to revise their relationships with their partners, reducing the number of reciprocal financial linkages. The analysis also suggests a sort of "reversion to the mean" movement during the last part of the sample indicating a return to the initial configuration.

As during the phase prior to the crisis shocks were small, the need for a country to enter into even more tight relationship increases and thus the probability to observe a reciprocated link became higher. On the contrary, during crisis periods, countries seem to actively reduce their reciprocal interactions and thus the number of non-reciprocal dyads intensified. Such behavior might be driven by an attitude to adopt a kind of *financial nationalism* – meaning that countries turn to policies systematically reducing foreign interaction.

We also found that the dynamics of most of the motifs can be better reproduced if the numbers of reciprocal edges are taken into account, being the z-score associated to the triads lower if random networks are generated using the RCM model. Thus the triadic dynamics can be traced back to the reciprocated node sequences which is more informative than the mere in-out degree distributions.

All these facts seem to support the fact that the topology of the IFN undergo major structural change as a crisis suddenly manifests, pointing out that the features of financial relationships are crucial to evaluate systemic financial integration. Furthermore, the changes occurring during crisis periods seem, in general, to be only temporary, even if such changes can last many years before returning to business as usual stages.

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